Entrepreneurs' Activities on Social Media and Venture Financing

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Abstract

Social media has been an incredible platform for startups to develop meaningful connections with stakeholders and customers. We investigate ways in which entrepreneurs use social media to drive both the level of engagement for their startup and the subsequent level of venture financing. Our empirical analysis demonstrates how differences in entrepreneurs' tweets—i.e., differences in the level informativity, persuasiveness, and transformativity—is associated with different levels of startup engagement and venture financing. We show differences in entrepreneurs' activity with the social media platform—i.e., the number of tweets, the number of mentions of other accounts, and the number of retweets—further drives engagement and venture financing. We test our model by collecting an extensive dataset of over 7,000,000 tweets from entrepreneurs and startups that have been through accelerators. Results indicate associates between the social media activities of entrepreneurs, startup engagement, and venture financing.

1. Introduction

Social media provides an incredibly powerful platform for startups and the entrepreneurs that power them to advertise and drive brand awareness without a large advertising budget. According to a report by Social Media Examiner (Stelzner 2015), in 2014, 96% of entrepreneurs use social media, with 92% of them confirming that social media has generated increased exposure and became important to their business. Edwards (2015) suggested that there are four primary goals entrepreneurs can achieve by employing social media, including driving brand awareness, distributing engaging content, generating leads, and enhancing customer acquisition. In some cases, entrepreneurs like Brandon Stanton (the creator of Humans of New York) or Rosanna Pansino (the CEO of Nerdy Nummies), etc., have successfully developed their entire businesses through their activities on social media.

Past research has indicated that startup's use of blogging tools is associated with increased venture financing (Aggarwal et al. 2012) and the emergence of blogs has been found to lead to an increase in firm founding's (Greenwood and Gopal 2015). These studies suggest the electronic word-of-mouth (eWOM) platforms like social media may have important economic impact for entrepreneurs and startups. However, specific investigation into the role of social media in startup outcomes has been extremely limited. In addition, we do not know which specific behaviors on social media that can be undertaken by entrepreneurs to drive important outcomes for their startups.

In this study, we address these gaps in the literature through a theoretical and empirical examination of entrepreneurs' activities on social media and the resulting level of venture financing. We test our model drawing from a sample of over 7 million Tweets by entrepreneurs and companies. Our empirical analysis demonstrates how differences in entrepreneurs' tweets—i.e., differences in the level informativity, persuasiveness, and transformativity—is associated with different levels of startup engagement and associated venture financing. Further, the model links entrepreneurs' activity on the social media platform—i.e., the number of tweets, the number of mentions of other accounts, and the number of retweets—with engagement and venture financing.

The paper proceeds as follows. We began by describing the overall theoretical model, linking electronic Word-of-Mouth (eWOM) effects and Twitter activities with startup outcomes. We then discuss the relationships between engagement and venture financing followed by the procedures used to test the model. We concluded this study by summarizing and explaining the results of our findings and discussed possible improvements for future research.

2. Theoretical Background

2.1. Entrepreneurs and Social Media

Entrepreneurs conduct a variety of activities through the process of launching a startup. One of the most relevant to the context of social media is the development of social relationships (Venkataraman 1997). These social relationships offer the potential of facilitating commercial activities for their startups, as

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key information can be transferred through social ties and social obligations (Shane and Venkataraman 2000). Research shows that entrepreneurs are often strategic regarding the development of relationships (Shane and Venkataraman 2000). To the extent that activities of the entrepreneur are conducted on social media, the platform provides the entrepreneur with the opportunity to more broadly maintain interactions with a larger group of potential customers or partners. Inertia suggests that emotional connections established with entrepreneurs will transfer to their startups (Webb et al. 2011) for developing different relationships. Thus, entrepreneurs' activities on social media is likely to positively influence the social media at the firm level.

2.2. Electronic Word-of-Mouth

Electronic WOM suggests that information communicated through person-to-person WOM channels is more reliable, credible, and trustworthy than marketing communication initiated by companies—i.e., advertising (Arndt 1967a, Arndt 1967b, Schiffman and Kanuk 2009). WOM communication consists of personal sources of product performance, purchase attitude, decisions, etc. (Cox 1963). Behaviors and attitudes of consumers can be influenced by being involved in WOM communications (Cox 1963, Brown and Reingen 1987, Money, Gilly and Graham 1998, Silverman 2011). Lau and Ng (2001) argued that messages communicated by WOM usually have multiple exchanges. When WOM is working well, a channel with one-to-one information exchange is established where firms' marketing messages are rapidly passed from one individual to another.

Work on WOM communication is extremely relevant for understanding eWOM in the context of social media, which provides three mechanisms of eWOM communications. First, social media provides a media platform, in which a company can release messages through the traditional one-to-many mass-media communication (Wattal, Schuff, Mandviwalla, and Williams, 2010; Dennis, Fuller, and Valacich, 2008). Second, as a social community, Mangold and Faulds (2009) found that on social media users are connected through mutual interest in a brand. Third, social media provide a rich context by which the effect of WOM communication can be strengthened—research that builds on media richness theory (Ngai et al., 2015; Dennis and Kinney, 1998).

2.3. Engagement

Engagement theories have proven useful in "the expanded domain of relationship marketing" (Morgan and Hunt 1994, Vargo and Lusch 2004, Vargo and Lusch 2008, Prahalad and Ramaswamy 2004). Relationship marketing helps to explain ways in which companies relate to existing customer, partners', and coworkers', and engagement is a link between the experience and the relationship outcome. Sprott, Czellar, and Spangenberg (2009) link consumer engagement with a brand and propose that brand engagement in the consumer self-concept is motivated by their emotional, cognitive, and behavioral interactions with brands. Hulbert and Capon (1972) consider the engagement as a factor of the interaction intensity given to an individual who participates or gets involved in activities offered by a firm. Moreover, Roberts, Varki, and Brodie (2003) bring forward that the engagement "reflects customers' interactive, co-creative experiences" with firms. Social media provides an information environment in which users have the opportunity to extend their relationship to brands through actions such as liking or following the brand.

3. Hypotheses

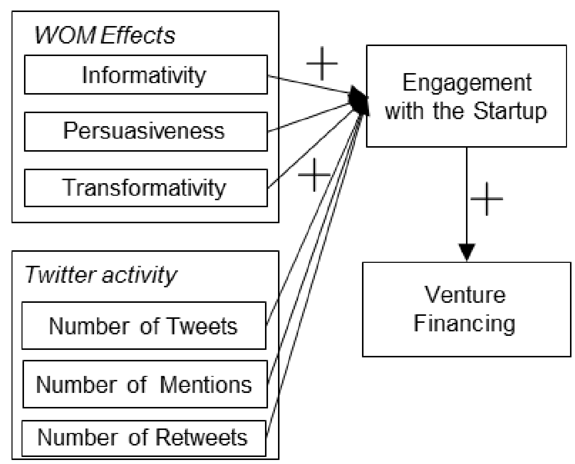

Figure 1. Concept Model

As indicated in Figure 1, social media platforms offer entrepreneurs a tremendous opportunity to drive engagement with in their startup, which will further be associated with increased levels of venture financing.

3.1. Engagement

In this paper, we clarified the engagement as the engagement with the startup and employed the working definition of Brodie, Ilic, Juric, and Hollebeek (2013), Webster, and Ahuja (2006). The engagement indicates that the amount of emotional satisfaction attached to the company would the users feel. The level of engagement with the startup is an effective measure to assess the firm's performance in the social media, since through being engaged with a company, online users will form an optimal attitude and behavior towards the company

(Mollen and Wilson, 2010; Webster and Martocchio, 1992). The engagement happening in consumer market will provide positive effects (Novak, Hoffman, and Yung, 2000), including increased exploratory behavior (Webster, Trevino, and Ryan, 1994; Novak, Hoffman, and Yung, 2000) and positive subjective experiences (Webster, Trevino and Ryan 1994, Csikszentmihalyi 1997). If the users, who act as investors, commercial partners, suppliers, etc., become more engaged with the company, it will increase the possibility that they will be involved in commercial relationship with the company, which will drive the business growth.

3.2. Twitter Activity

Research on Twitter activity is limited but growing. Hughes and Palen (2009) concluded that general Twitter provides an important platform for information broadcasting and brokering. Cho and Park (2011) suggest that Twitter serves as a communication tool for users' innovative activity. Moreover, while a user tweets/retweets, the message general includes three key features—informative content, internal citations (@ or mentions), and positive sentiment score (Desai, et al. 2012). These features will help users disseminating information effectively (Desai, et al. 2012). Users' posting and re-posting ("re-tweeting") behaviors can cause different levels of information credibility (Castillo, Mendoza and Poblete 2011).

There are several mechanisms through which entrepreneurs' social media activities on Twitter could be responded by users and have a positive influence on audiences' engagement with the startup. First, more activities imply that there will exist more possibilities for the level of engagement to be enhanced. Hoffman and Novak (1996) highlighted that online activities are distinguishingly featured on interactive effects, which can provide audience members with multiple roles, not only passive receivers of information, but also various roles as active participants or even "constructors" (Macias 2003). Advertisement researchers concluded that various activities of audiences facilitate their acquisition or control of company's information. Through this process, the audiences become engaged into the brand (Parsons, Gallagher and Foster 2000). Additionally, represented as an emotional engagement, users' sense of enjoyment should be reinforced, while a high level of activity creates a sense of autonomy and control in their minds (Jiang and Benbasat 2007).

H1a. Entrepreneurs' number of tweets is positively related to the engagement with their startup.

H1b. Entrepreneurs' number of mentions is positively related to the engagement with their startup.

H1c. Entrepreneurs' number of retweets is positively related to the engagement with their startup.

3.3. WOM Effects

In WOM communication, marketing messages are transferred into the information communicated by online users. The features, objectives, and effects of marketing messages are varied in each individual piece of information, which drive formation of different attitudes of online users toward the information environment brought in the message. Entrepreneurs use social media tor release information related to their company. As these information are communicated within the entire online community, users will be engaged with the entrepreneurs and their company. Therefore, we posit that *marketing effects of entrepreneurs' WOM communication on social media will generate positively influence on the user engagement with their startup.*

Moreover, marketing effects will be differentiated in each piece of information, and, consequently, will generate different influence on users' engagement. Previous studies have classified the marketing effects of WOM communication in three main types: informativity, persuasiveness, and transformativity. (Mehta, Chen, and Narasimhan, 2008; Bagwell, 2007; Machedon, Rand, and Joshi, 2013). Since we deploy this study in Twitter, the tweets posted by entrepreneurs will be the main carrier of the marketing message. We borrow these three types to classify the WOM marketing effects in tweets as follows:

Informativity: This tweet provides novel information about the startup.

Persuasiveness: This tweet increases willingness to follow the startup.

Transformativity: This tweet enhances happiness about being associated with the startup.

Moreover, relationships between these three marketing effects and the engagement can be posited as follows:

H2a. Informativity is positively related to the engagement with the startup.

H2b. Persuasiveness is positively related to the engagement with the startup.

H2c. Transformativity is positively related to the engagement with the startup.

These three types of marketing effects will generate different impacts on the engagement with the startup. First, informativity is the most fundamental marketing effect (Chu and Kim, 2011), which will drive users to raise awareness and knowledge of the brand when they receive intentional marketing information related to that brand, (Mehta, Chen, and Narasimhan, 2008). Informational influence is used to guide consumers interest in a product, brand, and store search, intentional or unintentional (Bearden et al., 1989; Deutsch and Gerard, 1955). The more relevant of the marketing information to the brand attributes is more verifiable. As such, they have a higher chance to engage consumers with the brand since consumers can have higher confidence in informed assessment of the brand's quality (Nelson 1970, Nelson 1974, Holbrook 1978, Mehta, Chen and Narasimhan 2008).

Second, in the context of a persuasive message, the engagement with the brand will be enhanced and, generally, be stronger than the engagement obtained in the context of informative message, mainly because the engagement is thought to intensify processing of the advocacy of the brand (Lee, Keller, and Sternthal, 2010). Comparatively, the engagement caused by persuasive effects is supposed to be related closer to a cognitive and cogitative process involving a brand, while the informative effect is highlighted under the role of usefulness (Rohm, Gao, Sultan, and Pagani, 2012) and knowledgeability. Petty, Cacioppo, and Schumann (1983) pointed out that even on the peripheral route to persuasion dominates, consumers' attention is concentrated on execution elements of the brand but not limited in informative value added in the message. Consumers could get engaged into the brand through a direct enhancement of their evaluation of the brand without cognizing attributes of the brand (Aaker and Norris 1982, Zajonc and Markus 1982, Mehta, Chen and Narasimhan 2008). Therefore, the first of additional hypotheses, describing the influence of marketing effects of WOM communication, is presented as:

H2d. Persuasiveness is more positively related to the engagement with the startup than informativity.

Third, in term of transformativity (Slovic, Fischhoff, and Lichtenstein, 1977), the consumer engagement approaches a higher level, an affectional connection with the brand (Mehta, Chen and Narasimhan 2008). In other words, informative and persuasive messages can only drive consumers to be aware of or keep in touch with the brand, while a transformative message leads them to go over both process and generate strong emotional connections with the brand. In this case, the engagement related to affections should be stronger than either engagement caused by informativity and persuasiveness. Previous researchers are also convinced that the deeper level engagement happens in the transformative process. Hoch and Deighton (1989) explained that this transformative effect should happen only after consumers overcome their biased perception toward the marketing information released by the company, mainly because the consumers consider that the engine of this marketing information (the company) attempts to gain interests from them and hence cannot be aligned with them in the market (Mehta, Chen and Narasimhan 2008). Consequently, this complicated process would shape an emotional transformation of consumers from biased, or even non-accepting, to the brand, to be happy for connecting with it. However, this process is not necessary present in the generation of either informativity or persuasiveness, which lead to a weaker form of the engagement than transformativity. Therefore, the second hypothesis of the influence of marketing effects of WOM is presented as:

H2e. Transformativity is more positively related to the engagement with the startup than informativity and persuasiveness.

3.4. Venture Financing

Researchers, such as Aggarwal et al. (2012), Greenwood and Gopal (2015), argue the social media may have important economic impact on entrepreneurs and startups through engaging different groups of online users, such as investors, advisors, etc. Aggarwal et al. (2012) discover that startup's use of blogging tools is associated with increased venture financing. Especially, engagement generated through bloggers' eWOM effect is a key element to decide whether ventures can obtain higher funding amounts and valuations (Aggarwal et al. 2012). Moreover, an alternative theoretical area argues that WOM and online activities could increase media coverage of crucial events, ideas, or firms, which would positively influence the legitimacy that ventures need to shape, when they pursue financial resources (Zimmerman and Zeitz 2002, Pollock and Rindova 2003). Engagement caused by WOM and activities acts as a substitute of unobtainable financial and fundraising data and thereby assists the startups in evaluating different ventures (Sanders and Boivie 2004). Emergence of different types of social media, such as blogs has been found to lead to an increase in firm founding's (Greenwood and Gopal 2015), which is marked as an important role of profitable performance from current diversified products and potential innovative markets (Zahra and George 2002).

Social media with its features, such as engagement, contributes to the improvement of venture financing (Brynjolfsson and Hitt 1996, Devaraj and Kohli 2003, Melville, Kraemer and Gurbaxani 2004). Information technology capability has been employed to answer how firms' integrated social media strategy can improve the firms' performance (Bharadwaj 2000) and consequently lead the increment of venture financing. According to weak tie theory (Granovetter 1973, Gilbert and Karahalios 2009), social media engagement enables entrepreneurs to dramatically increase the number of weak ties in their network and, consequently, access resources that enable their startup success. Similarly, based on social capital theory (Putnam 1993), social media's contributions to the performance of venture financing are mainly from engaging different types of social capital (Gaski 1986). For example, the social media strategy can be extended to serve the development of the customer relationship (Ray, Muhanna and Barney 2005). In the network era, the engagement between customer relationship and firm performance through social media is emphasized as an important factor in deciding the competitive advantage of a firm (Sambamurthy, Bharadwaj and Grover 2003). Therefore, our last hypothesis is formed as:

H3. The engagement with the startup is positively related venture financing.

4. Research Methodology

4.1. Data

Among several major social media platforms, we selected Twitter because: 1) Twitter, as one of the most popular social media in the world, not only engages majority of entrepreneurs and startups, but also links them to a massive user market in public with 310,000,000 estimated unique monthly visitors in 2015 (Alexa 2015); 2) Twitter's novel service, microblogging, has been agreed upon to contribute to eWOM marketing effects, since, with a few barriers during their communication, people can use a short time to come up with a short Tweet (composed of at most 140 characters) to express their emotional feelings about any commercial brand anywhere using various devices). 3) Investors have pay more and more attentions to Twitter activities of startups, and leverage the information they gather from social media platforms to evaluate startups and to break the information opacity (Hong 2013).

The sample contains 2,231 startup companies and 3,036 entrepreneurs selected from Seed-DB. Seed-DB is a large online datasets containing centralized information about high tech startups that have entered accelerators. Data from Seed-DB was matched with Crunchbase to provide detailed information about venture financing of each startup and links to the social media activity of the companies and their founders on Twitter. We collected Twitter data using the Twitter user timeline API. The collecting process keeps a circular queue of screen names and periodically checks updates of these users. By tracking 5,267 Twitter accounts of startups and entrepreneurs the final raw dataset included more than 10,000,000 historical tweets and above 2,000,000 retweets (from the day when they opened their accounts in Twitter to Aug 1, 2015). For entrepreneurs, there have 3,540,780 tweets, 864,730 retweets; for companies, the final dataset contains 2,358,258 tweets and 456,802 retweets. The maximum number of Tweets per account was 3,200, which is the upper limit of the API provided by Twitter.

4.2. Machine Learning

Our following data preparation procedure involved data cleaning, matching entrepreneurs with startups, and extracting variables relevant to the model. We proceeded to generate measures for informativity, persuasiveness and transformativity following the procedures outlined by Machedon, Rand and Joshi (2013). This procedure involved first randomly selecting 1,000 tweets as a training sample set. We asked three graduate students to rate each of the 1,000 tweets on levels informativity, persuasiveness and transformativity. The students were provided definitions of the three terms and rated the tweets based on their evaluation of how well the tweet's contents matches each definition. The Likert scale of each term ranges from 1 to 9.

To test internal reliability for different raters in this sample, we deployed Fleiss' kappa (Fleiss 1971). Fleiss' kappa of three items lies with the interval between 0.41 and 0.60, showing a moderate agreement among three raters (Landis and Koch 1977). Moreover, the majority of correlation coefficients between any two different items are below 0.2, indicating discriminant validity.

The next step was to train a machine learning algorithm to predict the class of each of the tweets in our dataset using the 1,000 classified tweets as a training sample. We used R and the packages "RTextTools" and "e1071" to build the classifiers. We split the 1,000 tweets into a training (80%) and a test (20%) set to evaluated the efficacy of various classifiers.

Results of different classifiers are listed in Table 1. Accuracy (Witten and Frank., 2005; Aggarwal and Zhai, 2012) is defined as a number showing how many test samples were correctly classified as compared to the total number of training results. Precision and recall (Davis and Goadrich, 2006) are also listed. The results overall suggested that Supervised Linear Discriminant Analysis (SLDA) provided the best classification results, providing the highest overall accuracy for the test set. This model was used to classify the remaining tweets from the dataset.

Table 1. Accuracy and Relevant Tests of Different Models

Items	Accuracy	Precision	Recall	F-Score
Maximum Entropy Classifier (Chieu and Ng 2002, Lu et al. 2006)				
Infor	0.2407	0.4000	0.4000	0.4000
Pers	0.1975	0.6549	0.6981	0.6758
Tran	0.1914	0.5842	0.6556	0.6178
Support Vector Machines (Dumais et al. 1998, Cai and Hofmann 2004)				
Infor	0.4012	NA	0.0000	NA
Pers	0.0123	0.6582	0.9811	0.7879
Tran	0.5556	0.5556	1.0000	0.7143
Elastic-Net Regularized(Fan et al. 2013)				
Infor	0.2963	0.4857	0.2615	0.3400
Pers	0.0802	0.6503	0.8774	0.7470
Tran	0.0556	0.5704	0.9000	0.6983

Supervised Linear Discriminant Analysis (Ye et al. 2006, Li, Zhu and Ogihara 2003, Spangler, May and Vargas 1999)				
Infor	0.4778	0.5571	0.5077	0.5306
Pers	0.6975	0.6325	0.6981	0.6637
Tran	0.6728	0.5636	0.6889	0.6200
Logistic Model Tree (Landwehr, Hall, and Frank, 2005)				
Infor	0.3827	1.0000	0.0462	0.0882
Pers	0.6543	0.6543	1.0000	0.7910
Tran	0.5556	0.5556	1.0000	0.7143
Bagging (Milne and Witten 2008)				
Infor	0.3765	0.4444	0.0615	0.1081
Pers	0.0062	0.6522	0.9906	0.7865
Tran	0.1728	0.5636	0.6889	0.6200
Logitboost Classification (Hassan and Hegazy 2015, Dogan and Tanrikulu 2013)				
Infor	0.3457	0.5294	0.1385	0.2195
Pers	0.4877	0.7941	0.2547	0.3857
Tran	0.4568	0.5714	0.1778	0.2712
Random Forest Classifier (Machedon, Rand and Joshi 2013, Malhotra and Jain 2012)				
Infor	0.3395	0.5263	0.1538	0.2381
Pers	0.0370	0.6579	0.9434	0.7752
Tran	0.0123	0.5677	0.9778	0.7184

Infor: Informativity. Pers: Persuasiveness. Tran: Transformativity

4.2. Variables

Our dependent variable (*funding*) is measured by the total funding the startup have collected as listed on Crunchbase. Engagement *(engm)* is measured by the summed of times the startup's tweets were forwarded (Kumar et al. 2013) over different time periods.

The three WOM effects—informativity *(infor)*, persuasiveness *(pers)*, and transformativity *(trans)*, were calculated by the machine learning method described above. Three different types of interactivity were the number of entrepreneurs' tweets (*twt*), the number of entrepreneurs' retweets (*retwt*), and the number of mentions or "@" (*ment*) the entrepreneur used in tweets. In the cases there were multiple founders, we calculated the mean across all cofounders to bring these measures to the company level.

We included control variables for 1) firm age, 2) the accelerating time indicating the age of the startup while getting into the accelerating program; 3) the size of the founding team; 4) the industry the startup belongs to (1 = high tech industry and 0 = biotech industry). In addition, we controlled for accelerator and year fixed effects (the year when the startup was established).

4.3. Analysis Method

We used the logarithm of both dependent variables, *funding*, and *engagement*, and added 0.001 to avoid the possibility of taking 0 (Ba and Pavlou 2002). The logarithmic transformation was employed, since both variables are positive integer data with a positively large skewed distribution. This transformation allowed us to make the variable yield normally distributed. In this case, an ordinary least square regression (OLS) model was carried to test the results. We also deployed the P-E fits (J. R. Edwards 2007) test to test the existence of different influence of three WOM effects.

4.4. Robustness Check

In addition, for examining the consistency of our result, we deployed the same models for the robustness test. For independent variables, we selected the data from the first one and two years after the startup has been established, since the mode number of startups' age in the dataset is 3. This means that in the original test, most samples would cover three years data. In the robustness test, we only used the two years' data on Twitter to measure the engagement, WOM effect and activities, and then matched these data with the dependent variable, the funding, which the startup received only during the same time periods, the first two years. By following this procedure, we would confirm whether the influences among the variables remain consistent over years, indicating internal consistency of both the dataset and the methods used in our analysis.

5. Results

The results of regression analysis are provided in Table 2. The analysis of the two models indicates a good fit with R-squared value of 0.3833 and 0.3438, and also produces a highly significant likelihood rate, where the p value is under 0.05. Additionally, the results are consistent between one year and two years robustness models, even though there exist minor differences.

Table 2. The Regression Result of Models

	Original Model		Robustness Model (1 Year)		Robustness Model (2 Year)	
	Dependent Variable					
	Engm	Funding	Engm	Funding	Engm	Funding
Engm		0.311***		1.568***		1.525***
		(-0.055)		(0.355)		(0.157)
twt	0.023**	0.007	0.333***	0.933***	0.351***	-1.118***
	(0.011)	(0.022)	(0.030)	(0.255)	(0.023)	(0.115)
ment	0.707***	0.117	0.011*	0.009	0.065***	0.036
	(0.251)	(0.482)	(0.006)	(0.043)	(0.012)	(0.053)
retwt	0.249**	-0.217	1.019***	-1.763**	0.307***	2.614***
	(0.110)	(0.211)	(0.094)	(0.805)	(0.050)	(0.230)
infor	1.235***	-0.079	1.823***	5.287***	1.951***	1.480
	(0.311)	(0.598)	(0.214)	(1.757)	(0.194)	(0.924)
pers	3.736***	-0.335	1.798***	0.835	2.901***	3.324***
	(0.736)	(1.422)	(0.216)	(1.768)	(0.189)	(0.962)
trans	6.764***	2.660*	2.032***	-4.313**	2.496***	1.471
	(0.776)	(1.530)	(0.224)	(1.852)	(0.182)	(0.905)
team size	0.227***	0.603***	0.024	0.177	0.022	0.031
	(0.049)	(0.095)	(0.015)	(0.114)	(0.014)	(0.061)
seed age	-0.092	-0.692***	-0.035	-0.383	-0.011	-0.123
	(0.069)	(0.131)	(0.041)	(0.309)	(0.030)	(0.133)
age	-6.070***	3.155	0.083	-0.500	0.069	0.103
	(1.901)	(3.653)	(0.067)	(0.513)	(0.058)	(0.261)
R^2	0.3833	0.3438	0.3872	0.3228	0.3893	0.3080

For the purposes of testing H1 and H2, we examined the influence of three types of Twitter activities and WOM effects on startup's level engagement. For H1a, H1b, H1c, the three variables, the influence of three types of interactivity, the number of tweets, the number of retweets, and the number of mentions are positive and statistically significant ($p<0.05$). Hausman Test result ($p<0.01$) confirmed that there is no endogeneity issue between twitter activities and funding. For H2a, H2b, H2c, the three variables, the influence of three types of WOM effects, informativity, persuasiveness and transformativity are positive and statistically significant ($p<0.01$). Therefore, H1 and H2 (a, b, c) are supported.

Moreover, to compare the different influence of three WOM effects, we need to test the relative size of the coefficients (J. R. Edwards 2007). Therefore, we first set three null hypotheses, in which we proposed that there are no difference among the coefficient size of these three variables. Then we deployed the P-E fits (J. R. Edwards 2007) test to test my null hypotheses. Thereby, the rejection of constraints indicated in null hypotheses is supportive for the conclusion that there is a difference between any two WOM effects. According to the P-E results, our p value of all three test is below 0.05 and F value is larger than the F critical value, implying we can reject the null hypotheses. The larger value of coefficient of transformativity implies that transformativity has a higher influence than the persuasiveness and informativity. Similarly, comparing to informativity, the influence of persuasiveness is larger. H2 (d, e) are supported.

For testing the influence of H3, we controlled the independent variables and performed a regression analysis. According to the result, the engagement with a company has a positive and statistically significant ($p<0.01$) influence on the startup performance.

6. Conclusion

This research provides a theoretical and empirical investigation of how entrepreneurs use of social media are manifest both in the impact on their company as well as the resulting level of venture financing. Specifically, results show significant impact of entrepreneurs' tweets (WOM effects) on important startup outcomes. We found that while informative, persuasive, and transformative tweets each were positively related to startup engagement. Transformative tweets have the strongest relationship with startup engagement in the main sample but the relative strengths of the coefficients were not consistent across the main sample and robustness check. As a result, we suggest more work is needed to understand ways in which the relative value of different types of tweets may correspond to different stages of company grown. Our results suggest that informative tweets are more important early in the startups lifecycle, but more work is needed.

In addition, we showed that an entrepreneurs' activities with the social media platform—i.e., the number of tweets, the number of mentions of other accounts, and the number of retweets—further drives engagement and venture financing. It is notable that the strongest influence of different types of interactivity comes from mentioning other people in the tweets. Mentioning suggests that the entrepreneur is not limited to indirect interaction with users by creating information or sharing their information, but instead directly interacts with users by starting or listening to a conversation. This direct interaction may help to develop real relationships via Twitter.

We investigated the relationship between startups' engagement and their venture financing. The result of H3 confirms that engagement has strong and significant influence on the venture financing. It is notable that this influence seems more powerful in the first two years, according to the result of robustness models. It implies that for startups, social media might be more valuable to help venture financing in their early stage. However, to prove this possibility, more work is needed.

7. Contribution and Discussion

Main findings and contributions related to these topics were as follows. First, we established that a positive relationship exists between entrepreneurs' eWOM strategy and their startups' social media engagement. Specifically, it is important to understand which kinds of marketing information that can drive the attraction of their startups the entrepreneurs should provide via social media. We confirmed that a class of communicated information categorized as *transformative* is the most supportive for the startup's online engagement. Furthermore, three broad categories of information, *informative*, *persuasive*, and *transformative* influence the increment of engagement differently based on different life stages of the startups. Second, we confirmed the positive influence of entrepreneurs' Twitter activities on their startups' engagement and demonstrated that the startup engagement is an important factor in the transfer of positive influence from entrepreneurs' eWOM effect and Twitter activity into venture financing. This provides a foundation in support of the importance of social media as a mechanism of startup success. Third, we first experimentally employed 8 machine learning methods. This enriches the methodologic foundation in support of the further related research.

As with any study, there are several limitations in this research, which could also open more opportunities for the future. First, although our final dataset includes more than 3000 startups, increasing the sample size to cover longer time periods should be really helpful for testing different the effects of different time periods. Future researchers could employ time series models or difference in differences (DID) that can more effectively tease out causal relationships.

In addition, our analysis could be extended to include more characteristic records of entrepreneurs' online behaviors. While we adopted an established brand-oriented framework for capturing how entrepreneurs tweet, there is an opportunity to develop alternate frameworks that help to capture what it is that entrepreneurs do on Twitter. Such a framework could be generated through a combination of topics based modeling.

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